



The Assessment of Customers' Credit Risk in Export Development Bank of Iran

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ABSTRACT

In recent years, many domestic banks have established risk management offices to manage their performances and customers' risks. The present study was carried out in order to manage, evaluate and reduce credit risks in Export Development Bank of Iran. Required data were collected from financial reports of 806 legal customers who are borrowers as well over 2008 to 2011. Test analyses were done using three methods including the Z-score, Logit regression and Neural Network. It is concluded that the Neural Network with 90.4% of prediction was able to classify the credit risks of customers better than other two models, i.e. Logit regression, with 89.6% and Z-score with 83.2%. In the prediction of default possibility, the efficiency of the Neural Network with 69.8% was higher than Logit model with 65.7% and Z-score with 45.9%. The results also showed that the ratios of free cash flow and assets turnover were considered as the most important ratios by all the three models. On the other hand, the efficiencies of Logit model and Neural Network method are the same calculating the prediction of customers' risks.

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1. Introduction

Studies of banks' credit risk management include assessment of credit risks, management policies and bank performances. Credit risk is considered to be an important issue which is taken into consideration of banking and financial industries. Ranking of credit risk is a potential risk prediction method that corresponds to credit portfolio. Therefore, several models can be used by financial institutions to assess risks. Banks can increase readiness to provide adequate credit policies using guidelines published by Basel Committee and international banks. The mentioned guidelines provide the possibility of effective management on banks' credit portfolio by identifying strategies, policies, and practices. It has been proven that banks with active and appropriate policies are able to improve the quality of their credit portfolio and minimize losses caused by the credit risk such as failure to repay loans (Fallah Shams & Rashno, 2008). Due to the importance of the subject, credit risk is controlled by evaluation of credit risk and customers validation in the form of a variety of informative and expert reports. When the receivers of the facilities are not able to fulfill their obligations, credit risk increases which causes economic losses for the bank; therefore, a prediction of appropriate structure for granting loans and fulfilling the interests of depositors, leads to decrease of credit risks (Jamshidi, 2011).

Theory and review of literature on credit risk will be explained in the following part. The hypotheses, data collection methods and analyses of hypotheses will be detailed using Altman's Z, regression, and neural network. In addition, the hypotheses test results using the three above-mentioned models and their comparison will be analyzed.

2. Literature Review and Background

In the developing countries, banks play a key role in the money market. Capital is needed for the production of intermediate and capital goods, and also the creation of infrastructure services which are considered necessary for development. Saving is the main source for capital formation, where more saving results in more simple conditions for investment. Capital formation and high savings and investment rates can lead to non-inflationary sustainable growth rate. Banking system generally effects economy through the mechanism of creation money, collection of savings, preparation of liquidity and payment ways and etc., as well as through creating equilibrium between investments and savings especially in the international sector. In fact, banks transform the unused capital of the individuals and

institutions into one of the basic factors of manufacturing in the form of bank deposits. Capital resource collection or mobilizing deposits and providing liquidity for investment in different economic areas and optimal capital allocation are the most tangible functions of the banking system.

Challenges of a bank risk management considered as intangible risks of income and also provided some basis for the risk modeling by scientific models. Therefore, since the banks are exposed to a variety of risks, management of assets and liabilities risks are the basic elements in banking industry, and the effective analysis of banks' activities requires sufficient assessment of the existing risks. In terms of banking and financial issues, risk is defined as the deviation from the expected results. From this point of view, any deviation from the expected results, either negative or positive is considered as the risk. The main categories of risks are classified as follows: financial risk, business risk, operational risk and the risk of accidents. Depositors and the possibility of withdrawing money by them, borrowers and their inability to repay their debts, the role of regulators in the stability of the bank, having possible claims on loans from objective and legal personalities which automatically transferring risks to the balance sheets and the public who pay ultimately the costs of financial crisis are categorized as the mentioned risks (Amini Zare, 2011).

Credit risk is considered when the borrower is unable to pay the loan and its interest according to the terms of the contract. In this case, the debt repayment will be either delayed or will not happen at all leading to cash flow problems in the bank (Falah Shams & Rashno, 2008). Credit risk is the most common reason for bankruptcy of banks which has caused policy makers and regulators to set minimum standards for credit risk management. Identification of the existing and potential risks in the nature of lending is the basis for proper management of credit risk. Measures to deal with these risks typically include a precise definition of policies that explain the philosophy of credit risk management and how to control credit risk factors. In particular, credit risk management encompasses three methods.

The first method indicates the formulation of policies aimed to limit or reduce credit risk, for instance policies on concentration and acceptance of high risks, adequate diversity, providing the loan to dependent members or being over exposure to risk. The second method includes a set of policies on the classification of assets. Applying these methods requires periodic and continuous evaluations of loans receivable portfolio and other financial

instruments. The third method consists of a set of policies for calculating doubtful accounts provisions or provisions for probable losses (Groening & Bratanovic, 2003, p 46).

The banks can do followings to cover and reduce credit risk: specifying the amount of securities and guarantees as the approval of the loan and asking the borrowers to provide their documents and guarantees in the form of house and personal properties and reliable guarantors. The value of securities and guarantees and creating risk cover for loans depends on the borrower's credit risk degree. Presumably, the higher risk probable the clients are, the more valuable securities are required.

On the other hand, banks can employ a selective monitoring system, in which closer monitoring is related to loans with high credit risk. Reasons of weak performance of the borrower and the following changes should be specified. To design the above-mentioned system, it can be helpful to conduct some research on high-risk applicants as well as holding periodic meetings with high-risk customers having outstanding debts, and the examination of the reasons for delaying and defaults. The investigation of the various industries and the consideration of the volume of their outstanding debts also helps the banks to recognize risky industries which leads to set some restrictions for the different industries.

The most common models for measuring the credit risk can be outlined as follow:

1. Econometric methods: These methods include multiple regression models of audit analysis and Probit and Logit analyses. In all these models the probability of the default or the loss on the loan defaults are considered as the dependent variable and financial ratios and other quantitative and qualitative factors such as management, competition, etc. are considered as independent variables.
2. Neural Networks model: Neural Network is the computer-based systems being like human brains that follows the interconnected neurons in decision making process. Neurons are the smallest units of decision making in the brain. The same data used in econometric techniques are applied to make appropriate decisions. Test and error methods are used in the decision making process in the neural network.

3. Optimization techniques: These techniques are mathematical programming models that consider optimal weight for loans and borrowers' characteristics to minimize the losses of the default and maximize profits.
4. Expert systems (rule-based systems): These systems follow the decision making process of the professionals by using structured methods. In other words, expert systems try to set experts' decision making process in the form of rules and guidelines within the organization, so that analyzing and making correct credit decisions is possible while they are not available.
5. Combined systems: These systems are a combination of the simulation, estimation, and calculation techniques for the extraction of scientific relationships between independent variables and the probability of default. The system parameters are determined based on estimation techniques (Fallah Shams & Rashno, 2008).

As well as Basel Committee studies, many studies are done by researchers and credit institutions to design accurate model of credit risk measurement. In addition, many models are used to measure credit risk in banks and credit institutions by using econometric methods and fuzzy and neural networks (Tehrani & Fallah Shams, 2005). A model of measuring and ranking credit risk was concluded on bonds in 1909 by John Murray for the first time (Glantz, 2003, p 87).

Credit rating agencies such as Moody's and Standard & Poor's uses specific methods for grading bonds and other credit instruments. Similarities of banks credit loans and leasing institutions to bonds guide some researchers to consider the ratings of the credit risk, i.e. measurement of the default risk of loan and its interest (Fallah Shams & Mahdavi Rad, 2010).

One of the first studies on the measurement of credit risk on the firms' bonds was Altman's scoring multivariate model that was performed in 1968 and was known as Altman Z-score model. Altman Z-score model is an auditing analysis model which uses the financial ratios to list companies with financial issues. The model was used to predict the credit risk of the borrowers by Sanders and Alan. A review of the performed studies showed that the model is highly applicable for predicting credit risk (Saunders & Allen, 2002, p 126).

Emel .A.B. et al (2003) proposed a credit scoring methodology based on Data Envelopment Analysis (DEA). Financial data included 82 industrial production companies that constituted the credit portfolio of one of the biggest banks in Turkey. 42 financial ratios were selected based on a literature review in this study, among which 6 financial ratios were considered of high importance. After validation of the model by regression analysis, they found that DEA method was able to estimate the credit ratings of companies efficiently.

Limsobunchai, Gan and Lee (2005) carried out an analysis of credit scoring for agricultural loans in Thailand. They have used the model and two types of artificial Neural Network models, one of which is called as the Probabilistic Neural Network (PNN) and the other as a Multi-layer Feed Forward Neural Network (MLFN), to estimate credit scoring model. In this study, the predictive power of each of the three models were estimated experimentally. The results suggest that the correct predictive power of PNN model is higher than the other two models.

Khashman (2010) in a research regarding the effect of neural networks to assess credit risk, studied the issue of credit ratings of the borrowers. Using 24 effective numerical factors, he has concluded that neural networks model is more effective for rating borrowers.

Salchenberger, Cinar and Lash (1992) carried out a study regarding the prediction of financial institutions' crisis using the Neural Network and they also compared their results with model. They used five financial ratios such as capital adequacy, assets quality, management efficiency, profitability, and liquidity. They selected 100 samples of bankrupt and 100 samples of the non-bankrupt institutions based on geographical locations and the value of assets from 1986 to 1987. The results showed that the Neural Network model predicted bankruptcy more effectively than the Logit model.

Although risk management in banking system has been considered as importance during the last decade in Iran, few banks have had an independent office for risk management which is very limited comparing to other countries.

Gholizadeh (2004) has reported the ranking of companies using Analysis Hierarchy Process (AHP). Views of experts on the importance of financial variables to rank the firms were identified by using measurement method, and then the food companies have been

ranked using AHP method. The results showed that the mentioned approach is a proper way to rank companies in terms of risk.

Zekavat (2002) classified legal clients of Export Development Bank of Iran in terms of credit risk using Logit model and auditing analysis method. According to the results, the auditing analysis and logistic regression methods present relatively similar results in relation to the classification of firms in terms of credit risk. Current ratio was the most effective financial variable in customer segmentation.

Mansouri (2003) analyzed credit risk and credit capacity of companies and loans demanding organizations using a set of independent variables and Multi-layer Perceptron Neural Networks. In order to assess the efficiency of Neural Network model in comparison to the classical models, the results were compared with those of linear and logistic regression models. The results showed that Neural Network and logistic regression models have similar capabilities to estimate credit risk, but Neural Network model is more applicable to estimate customers' credit capacities.

Arab Mazar and Ruintan (2005) employed Logit regression to identify factors affecting customers' credit risk of Agricultural Bank. For this purpose 36 explanatory and independent variables were recognized and employed using 5c method. Finally, 17 effective variables were concluded. Liquidity and current ratios have the greatest impact on customer segmentation into two groups of companies: companies with high credit risk and companies with low credit risk.

Taghavi, Lotfi and Sohrabi (2008) in a study to explain a method for credit rating of the bank customers, revealed the process of helping credit risk measurement, its management, and control. Therefore, models used in the ranking of customers and the experience of some foreign banks were presented. The Logit statistical method was used for assessing the effectiveness of quantitative and qualitative variables in the customer credit records. To evaluate the effectiveness on the prediction of crisis 15 variables were used and finally 7 variables were identified as practical ones. The history of customers considered as the most significant factor.

Nily and Sabzevari (2008) estimated and compared Logit credit rating model, using Analysis Hierarchy Process. Credit rating model is defined as a model on the basis of

quantitative criteria to measure clients' histories. A score is dedicated to each customer recognized as an indicator of customers' risk. Two models, the Logit model and Analysis Hierarchy Process, have been used considering the final accuracy of Logit model to evaluate the credit risk was 78%. Analysis Hierarchy Process model is able to estimate properly, even though the volume of information would be low.

In the present study, logistic regression econometric method is one of the best methods due to evaluation of the effect of qualitative and quantitative variables on the two-level dependent variable. Neural Network approach is also one of the most efficient methods of decision making which is used extensively in the field of credit risk assessment in the last decade.

3. Research Hypotheses

This study aims to evaluate credit risk of legal clients of Export Development Bank of Iran using various statistical methods and comparing them in terms of their efficiency and accuracy. Based upon the literature and research background to achieve the objective, following hypotheses are developed:

1. The customers' credit risk of Export Development Bank using Logit econometric is predictable.
2. The customers' credit risk of Export Development Bank using linear estimated Altman Z score is predictable.
3. The customers' credit risk of Export Development Bank using Neural Network model is predictable.
4. Artificial Neural Network method is the most accurate model in the prediction of customers' credit risk of Export Development Bank.

4. Statistical Population and Research Data

The statistical population consists of all legal clients of Export Development Bank getting loans from 2010 to 2013 including 806 legal clients who have valid financial statements. Thus, in regard to the limited statistical population size, all members have been studied using census. The data include information in the financial statements and qualitative information of each borrower in which explanatory variables have been extracted from. The dependent variable is considered as the probability of default and un-default; therefore, in the case of default, the value equals to zero, otherwise, it is one.

5. Methodology

The present study is an applicable research in terms of the objective since its results can be used by managers and policy makers of banks and financial markets. The efficiency of different models in the prediction of credit risk is studied and compared. Also the relationship between customers' financial characteristics and the risk of banks are examined. Thus, it is considered as a descriptive correlational study. The methodology of the research consists of several steps as the follows:

1. Identifying variables affecting the status of no-defaulted and defaulted borrowers;
2. Classifying customers into two groups of no-defaulted and defaulted based on criteria and guidelines of Basel Committee or Central Bank of Islamic Republic of Iran;
3. Assessing the model's efficiency to estimate the customer's credit status by classification made by the related banks so three different models are used.

5.1 Altman Z Model

Altman applied multiple auditing analysis as a statistically suitable method for classification of each variable in the groups of bankrupt and non-bankrupt to find their financial problems. He selected 5 financial ratios among 22 ratios which were considered the best variables to predict bankruptcy. He presented the Z value in the form of a function in which the variables x_1 to x_5 are as follows, respectively: working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, book value of equity to total liabilities, and sales to total assets.

$$Z = 0.717 X_1 + 0.847 X_2 + 3.1 X_3 + 0.42 X_4 + 0.99 X_5 \quad (1)$$

5.2 Logit Method

Logit regression model applies logistic curves to identify two or more distinct groups. The predictor variables are measured using qualitative and quantitative scales and the dependent variable is a qualitative and two-side one. These two categories usually refer to membership or non-membership in a group. The occurrence probability and non-occurrence probability of an event are shown by (p) and $(p-1)$, respectively. Logit regression model is defined as follows:

$$Z = \ln \left(\frac{p_i}{1-p_i} \right) = \beta_0 + \sum_{i=1}^n \beta_i X_i \quad (2)$$

The dependent variable is default or non-default of loans of customers, while default is assigned a value of zero and non-default a value of 1. There are 11 quantitative independent variables (financial ratios) and 5 qualitative independent variables in the model. The model is evaluated as follows.

Overall Significance testing in the regression

The following hypotheses have been considered for testing the model:

H₀: The assumed model is not consistent with data

H₁: The assumed model is consistent with data

Chi square test (χ^2): It will be ideal if the null hypothesis is rejected considering α is 0.05, in which case the model is well fitted. If the significance level is smaller than 0.05, the null hypothesis can be rejected and consequently the model is consistent with the data.

Hosmer-lemeshow test: The values predicted by the model are compared with the actual observation values. If the significance level of this test is greater than 0.05, the null hypothesis is rejected which means the model has provided acceptable explanation of data (shirinbaksh et.al., 2011).

Nagelkerke R^2 index: It is impossible to compute R^2 in the logistic regression, so the Nagelkerke R^2 index is used as an approximation of R^2 in the typical regression.

Regression Coefficients Significance Testing

The significance of the logistic regression coefficients is determined using Wald Test which has the distribution of χ^2 with one degree of freedom. If the significance level for all coefficients is less than 0.05, the null hypothesis is rejected for all coefficients at 95% confidence level and consequently the coefficients are significant.

Estimating the Efficiency of the model

The efficiency of the model is obtained by dividing the correct estimates by the total number of data as the percentage of the correct prediction for each group of zero and one, and the total.

Neural Network System

In fact, an Artificial Neural Network system simulates human learning process. ANN system tries to learn the relationship between data (financial ratio, economic process, management quality, and etc.) and outputs (credit status of borrowers) by mimicking the human nerves and brain system, through sampling repetition of the previous set of input/output data. ANN system has a major advantage compared to the expert system. When data are not complete or are noisy, it makes a reasonable guess of data using previous patterns. ANN is specified based upon the three factors including input, synaptic weights, and hidden layers (Sanders & Allen, 2002, p 192).

Implementation of Neural Network model consists of two phases: training and testing. First, 70% of the samples are included in the training set and 30% in the testing set. According to the data of the testing set, the model finds and learns the patterns existing in the data, and measures its learning against the training set to obtain its error and makes it less and less through changing the weights in each step. So the prediction table consists of two parts, one of which relates to the training set and the other to the testing set.

6. Results and Findings

6.1. Altman Z Model

The results of Altman z model have been reported in Table 1. The correct prediction was estimated equal to 45.9% for group whose loans were defaulted, and 94.1% for the non-default group. Thus, the correct prediction of the whole model was estimated equal to 83.2%, which is presented as Altman Z prediction power.

Table 1
Results of Altman Z model estimation

Group	Number of predicted group		Total number	Percentage of the predicted group		Total accuracy of the model %
	Number of Default	Number of No-Default		Default %	No-Default %	
Default	137	161	298	45.9	54.1	83.2
No-Default	7	111	118	5.9	94.1	

6.2. Logit Regression Model

In order to design an optimal model for measuring credit risk, 16 explanatory variables including 11 quantitative and 5 qualitative variables were included in the model and furthermore, Logit regression was estimated using the SPSS21 software. Variables which were not statistically significant were omitted and the final model consisted of 5 significant quantitative variables and one significant qualitative variable. It should be noted that the model was first estimated using intercept and due to insignificance of the intercept, was excluded and the final model was estimated without using model intercept. The results of the final model are shown in Table 2.

Table 2
Results of Logit model estimation

Variable	Coefficient (β)	EXP (β)	WALD test	P-Value
Total Debt to Total Assets	-3.633	0.026	53.272	0.000
Retained Earnings to Total Assets	10.907	52557.28	15.486	0.000
Net Income to Total Assets	45.093	383500	42.989	0.000
Sales to Total Assets	2.533	12.595	50.248	0.000
Financing Cost to Gross Profit	0.295	0.745	2.732	0.098
Economic Sector	1.444	4.252	20.451	0.000
Chi Square Statistic	796.63	Hosmer-Lemeshow Statistic		5.141
P-Value	0.000	P-Value		0.742

Based on Table 2, the estimated model can be defined as follows:

$$Z = \ln \left(\frac{pi}{1-pi} \right) = -3.633X_1 + 10.907X_2 + 45.093X_3 + 2.533X_4 + 0.295X_5 + 1.444X_6$$

The probability of default of loans received by each client can be also written based on the following equation:

$$P = [1 + EXP\{-3.633X_1 + 10.907X_2 + 45.095X_3 + 2.533X_4 + 0.295X_5 + 1.444X_6\}]^{-1}$$

Considering the Chi-square statistic calculated in Table 2, with the value of 796.63 and the significance level of smaller than 0.05, it can be concluded that the fitted model is consistent with data, so rejected the null hypothesis. Also, the value of Hosmer-Lemeshow Test with χ^2 distribution, was calculated equal to 5.141 and its significance was 0.742, greater than 0.05, thus, the model has provided an acceptable explanation of data.

On the other hand, the results show that significance of logistic regression coefficients are determined using Wald statistic with χ^2 distribution of one degree of freedom. Considering confidence level as 95% all variables are significant except the financing cost to gross profit which can be accepted at 90% confidence level.

6.3. Neural Network Method

A summary of the Neural Network process carried out using the software shows that out of 806 observations, 550 for network training and 256 for network testing are allocated, which means 68.2% of the total observations are considered for training samples and 31.8% for trial ones. The information show that the input layer consists of 23 units which is equal to the number of covariates plus the total number of operating level. A separate unit has been considered for each qualitative variable. Also a separate output unit has been considered for each of the customers who have the history of no-default, including two units in the output layer in total. The designed network architecture is also indicating the existence of one hidden layer which contains 6 units.

The summary of the model shows that entropy error, which the network tries to minimize during its process, will be equal to 110.95 and 64.61 during the training and testing phases, respectively. It is obvious that the smaller values of the error are more desirable. The percentage of incorrect prediction has been 9.6 percent during the training phase and 12.1 percent during the testing phase.

Table 3
Classification of the Neural Network model

Phase	Observation	Default	No-Default	Correct Prediction %
Training	Defaulted Customer	67	29	69.8
	No-Defaulted Customer	24	430	94.7
	Total			90.4
Testing	Defaulted Customer	20	27	57.4
	No-Defaulted Customer	11	198	94.7
	Total			87.9

According to the results in Table 3, 430 out of 454 cases which have been No-defaulted customers in the past, have been classified correctly and 67 out of 96 cases which have been defaulted customers in the past, have been also predicted correctly considering the training model. Generally 90.4 percent of the training phase cases have been properly classified. Network has acted better to predict customers who have refunded their received loans (No-defaulted customers).

Out of 209 observations which have been used for testing the model, 198 cases have been no-defaulted customers which have been predicted correctly and among 47 cases who have defaulted in the past, 27 cases have been classified correctly. In general, 87.9% of all samples were correctly predicted. Network has also acted better in the prediction of no-defaulted customers.

Table 3 indicates that the degree of sensitivity and specificity of the model equals to 94.7% and 69.8%, respectively. The value of credit risk, namely classification of defaulted customers to no-defaulted customers was estimated equal to 30.2 percent and the value of business risk, namely classification of the no-defaulted customers to defaulted customers was estimated equal to 5.3 percent. Also according to the results of neural networks testing phase, the degree of sensitivity and specificity of the model will be equal to 94.7 and 57.4%, respectively and the value of credit risk and business risk can be obtained 42.6 and 5.3 %, respectively.

7. Comparison of Models Efficiency

Table 4 shows a summary of results relating to the performance of three estimated models including Altman's Z, Logit regression and neural network. The default group with 69.8 percent and no-default group with 94.7 percent have been predicted by the Neural Network model and 90.4% of the total sample has been correctly classified. It should be noted that this model has predicted the no-default group more accurate.

It is seen that Logit regression model has predicted the default group with 65.7 percent and no-default with 94.2 and it has classified 89.6 percent of total samples correctly. The no-default group is predicted in a better way than default group. The results show that Altman Z model has also predicted the default group with 45.9% and no-default group with 94.1% and also in total 83.2% of the whole samples has been correctly classified. Similar to other models, the default group has been predicted in a better way than the no-default group.

Table 4
Comparison of models efficiency: Neural Network, Logit, and Altman Z

Model	Correct prediction (%)		
	Default group	No-Default group	Total
Neural Network	69.8	94.7	90.4
Logit regression	65.7	94.2	89.6
Altman Z	45.9	94.1	83.2

It should be noted that in comparison to all models, generally Neural Network model predicting 90.4 percent has been able to classify the customers of Export Development Bank better than the other two models, namely logistic regression with 89.6% and Altman Z with 83.2%. But according to unmarked differences of the prediction percentage between Neural Network and logistic regression models, it can be concluded that both models are appropriate to predict credit risk. Moreover, respecting to the percentage of predictions, 94.7, 94.2 and 94.1 percent, the ability of all three models in prediction of no-defaulted customers is close to each other, but in the prediction of defaulted customers, the ability of Neural Network model with 69.8% is higher than Logit model and Altman Z model with 65.7 and 45.9 percent, respectively. Thus the three models have acted better in predicting no-defaulted customers compared to defaulted customers. Considering the importance of default prediction for banks and due to higher ability of Neural Network model in the better prediction of this group, it can be concluded that the model is more appropriate to predict the credit risk than the rest of them.

8. Summary and Conclusion

Table 5 presents a summary of the results of three models including Altman Z, Logit regression and Neural Network to predict the credit risk of the bank customers.

Table 5
Summary of results of three models

Models	Altman Z	Logit Regression	Neural Network
Correct Prediction	83.2%	89.6%	90.4%
Sensitivity (No-Default)	94.1%	94.2%	94.7%
Specificity (Default)	45.9%	65.7%	69.8%
Credit Risk	54.1%	34.3%	30.2%
Business Risk	5.9%	5.3%	5.3%

Table 5 indicates that the overall accuracy of Altman Z model prediction has been estimated 83.2 percent. The degree of sensitivity equals to 94.1 percent, which means the accuracy of prediction of no-defaulted customers and the degree of its specificity has been estimated equal to 9.45 percent, which shows the accuracy of the prediction of defaulted customers. The value of credit risk, namely classification of defaulted customers within the no-defaulted customers (one minus the degree of specificity), and the value of business risk, namely classification of no-defaulted customers within the defaulted customers (one minus the degree of the sensitivity), have been estimated 54.1 and 5.9, respectively.

The overall performance of Logit model which was represented as the percentage of the accuracy of model prediction equals to 89.6 percent. It can be observed that the degree of the model sensitivity and specificity are obtained equal to 94.2 and 65.7 percent, respectively. The value of credit risk and business risk has been also estimated equal to 34.3 and 5.3% respectively. The results of Neural Network model also shows 94.7 percent (sensitivity) for those who have no history of default in training phase, classification has been done correctly and 69.8 percent (specificity) of the cases who have been defaulted customers in the past, have also been predicted correctly. In general it can be seen that 90.4 percent of the training phase cases have been predicted correctly. Also, the value of credit risk and business risk has been estimated 30.2 percent and 5.3 percent, respectively.

In the comparison to three models, it is noteworthy that Neural Network model generally has been more practical compared to the other models to classify the customers of Export Development Bank. The ability of all three models to predict no-defaulted customers is close

to each other, but in the prediction of defaulted customers, the ability of Neural Network model has been higher compared to Logit model which is considered to be more practical than Altman Z model. Thus, it can be said that regarding to the significance of the probability of default prediction and default loans in credit risk, due to the higher degree of specificity of Neural Network model compared to other models, this model is more efficient. The research findings also showed that the performance of three models in predicting no-defaulted customers has been much higher than defaulted customers.

9. Recommendations

According to the results obtained in the estimation of credit risk using Logit regression, it was observed that the ratio of return on assets has the greatest impact on credit risk; thus, it is recommended to lenders to pay special attention to this financial ratio in credit decision making and credit metrics of their customers. Considering high credit risk in industrial sector compared to other sectors, it is recommended to customers for obtaining sufficient guarantees.

According to the results of Neural Network model, banking system administrators can be offered to use this method for estimating credit risk of the bank loans portfolios. With identifying and defining multiple independent variables that seems to be effective in default or no-default of the received loans, only the effectiveness or lack of effectiveness of each of these variables and the amount of relative effectiveness of each on the dependent variable which is repayment or default of the loans, are evaluated.

Since the ratio of debt, free cash flow, return on assets, asset turnover and interest coverage ratio, were recognized as the most important variables to classify customers into two groups of defaulted and no-defaulted customers in Logit and Neural Network models testing and both models have had high precision and performance, it is recommended that the managers of Export Development Bank to take aforementioned ratios into account for investigating the requisition of customer loans and providing experts' reports, and also prioritize them easily using Neural Network. Since the output of Logit method is based on the function with certain coefficients which is one of the reasons for being prior over other methods, so it is recommended to use a comprehensive sample involving of entire banking system and credit institutions for estimating customer credit risk in the future research.

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